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ABSTRACT

Expert systems are computer programs that are designed to advise or assist users by storing the knowledge of human experts and applying the computer's mathematical ability to search and sort this information. This study investigated the use of an expert system as a mindtool and whether or not creating a simple expert system would facilitate the formation of an accurate mental model of a system. The domain selected for the study was that of hydraulic brake drums. Participants were 33 adult males and females from a variety of professions located in the United States, Canada, and the United Kingdom. Results indicate that creating the expert system substantially increased participants' scores on all three measures of mental models. In addition, participants indicated that using the expert system focused their attention on the topic and that it was fun to use. Network similarity scores increased significantly, with a large effect size, during the midtest to posttest period during which participants created the expert system. Scores on a test of troubleshooting increased significantly, but with only a medium effect size. Results of a prediction test also indicated that the use of an expert system facilitated the development of more expert-like knowledge structures. Expert systems appear to be versatile and powerful mindtools. (Contains 8 tables, 6 figures, and 59 references.) (SLD)

Expert Systems as a Mindtool to Facilitate Mental Model Learning

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INTRODUCTION

Expert systems are a genre of computer programs that are designed to advise or assist users by storing the knowledge of human experts and applying the computer's mathematical ability to search and sort this information. Expert systems provide decision-making advice to humans in the absence of available human experts (O'Hara & Shadbolt, 1997).

Expert systems have an advantage over conventional computer programs in that they incorporate domain knowledge in their rules and data, rather than inculcating it in the program code. This permits expert systems to be used to solve many problems within the knowledge domain without expensive reprogramming of computer code. Traditional programs have a single fixed set of procedures written into their executable code. This governs what the program does, and limits what the program can do without rewriting of part or all of that code. Expert systems, conversely, have two main parts: programming that contains knowledge and logic in a domain, and an inference engine that uses the facts and logic to create conclusions, solutions, or recommendations. This permits the flexibility to use selected parts of the knowledge as required for a given situation. It also permits addressing many aspects of a problem within the domain of the knowledge (Medsker, 1995).

The ability of expert systems to explain their reasoning processes, by displaying the facts and rules applied to come to a certain conclusion, also distinguishes them from conventional computer programming (Law, 1995). When asked by the user, an expert system will display which rules and which facts it used to come to the conclusion or solution presented. Conventional computer programs simply execute the lines of code, as written by the programmer, without explanation or justification. Expert systems today are used in numerous businesses, industries, professions, and academic settings. These systems function as advisors, decision support tools, diagnosticians, and as tools for exploring human cognition (Shipley, 1989). It is in the last role that expert systems are being studied as learning tools, and are considered to be one of the most promising mindtools for use in classroom situations (Jonassen, 1996).

Expert Systems as Learning Tool

Mindtools in instructional theory, according to Glaser and Bassok (1989) and Glaser (1990), are concerned with three kinds of learning: (a) learning that derives from the performance of a skill once it has been acquired, (b) learning that capitalizes on intrinsic motivation by engaging the learner in a challenging task, and (c) learning characterized by increasingly sophisticated and elaborate mental models that mark the learner's gradual mastery of a new domain (p. 30).

Jonassen (1996) limits mindtools to tools and learning environments that are computer-based and are intended to promote higher-order learning and problem solving. Mindtools do this by four means: (a) supporting cognitive processing, (b) extending the thinking processes of those using them, (c) making the learner an intellectual partner with the computer, and (d) facilitating the learner's own construction, interpretation, and organization of knowledge and information. Mental models, a form of learning outcome associated with success in problem-solving and higher-order learning can be created as a result of the use of mindtools (Willie, 1990).

Classroom Expert Systems

Expert systems have been used in the classroom, at almost all levels of education, as tools for learning. Expert systems can be constructed by teachers as tools for student use or by students as tools for learning. In an undergraduate statistics class, the instructor created an expert system with two purposes in mind: (a) to outline and organize his/her thoughts in a structured fashion while developing the system, and (b) to provide a tool for students to use to assist them in selecting the appropriate statistical procedure to use in a narrowly defined situation (Karake, 1990).

Building on the Karake (1990) study, Saleem and Azad (1992) developed both modular and integrated expert systems to demonstrate their application in instructional environments as CAI tools. The modular system more closely approximated traditional computer-assisted instruction through which a student proceeds in a linear fashion from module to module. The integrated system allowed the student more flexibility in moving from one part of the lesson to another

Students in grade two through graduate and professional schools have been assigned projects involving the use and creation of expert systems to enhance the process of learning. Jonassen, Wilson, Wang, and Grabinger (1993) reported that the people who learn the most from the design and development of instructional materials such as expert systems are the designers themselves, by articulating and structuring their knowledge about the domain in which they are creating the expert system. This type of design causes the creator of the expert system to reflect on his/her knowledge in new and meaningful ways. This perspective was reflected by Salomon (1993) when he postulated that learners learn and retain the most from a body of knowledge by what he calls "mindful engagement" (p. 27). This occurs when students must represent what they know using some particular application. The creation of expert systems allows and fosters symbolic representations of knowledge of things and heuristic knowledge that model the way people solve problems in real life (Sener, 1991).

Expert Systems as Pedagogical Tools

Students have constructed expert systems to facilitate their learning within a relatively narrow domain of knowledge. An unusual departure from applications in which expert systems contain the knowledge of experts, was a study of twelve students (no control group) who constructed expert systems from their own intuitive expertise rather than the acquired knowledge of a domain expert. The purpose of this study was to explore the student's process of commonsense reasoning. Based on the premise that "a good context for eliciting in-depth reasoning in a nonthreatening way is one in which the subject plays the role of a teacher" (Law & Ogborn, 1994, p. 498). This concept of 'teaching the computer' through creation of an expert system using the student's own knowledge accrues the benefits of displaying the student's knowledge through content of the expert system knowledge base, showing the student's patterns of reasoning through configuration of the rules created within the system, and perhaps even some insight into the general structure and processes of the student's cognition through the elements of explanation the student building into the expert system.

To teach 101 students in fifth grade about environmental problems, classroom teachers and university researchers collaborated in producing an expert system-based multimedia tool that provided students with a situated learning experience (Okamoto, Kawashima, & Miyame, 1994). Using this system, the student hypothesized about environmental problems in a city by building that city, arranging infrastructure elements, and deciding policy, much as a city mayor would do. The expert system then advised on results and consequences, and provided advice on rearranging the city and its parts. The teachers found that the students were very enthusiastic about this mix of media, and that the pupils' attention was held longer than with traditional methods.

Working with students in grades two through six, Tamashiro and Bechtelheimer (1991) used expert systems as a student to which their students "taught" certain simple facts and concepts about stick figures. The expert system was then used to diagram the relationships among concepts through the tree diagram created by the system. Tamashiro and Bechtelheimer reported observing an increase in self-confidence in the students as a result of the use of the expert system. No control groups were reported as being used in their studies that the authors referred to as field trials.

Knox-Quinn (1988) used a group of 27 junior high school students (no control group), in a summer seminar setting, to construct knowledge in a domain of their choosing, and then to convert that knowledge into an expert system. It was found that by so doing, even though this was a brief two-week, hour-a-day summer seminar, students were able to construct remarkably detailed experts systems. The pre-teen and teenage students also reported having great fun doing these projects. It was noted that, because the students chose a very diverse range of topics from how to select shoes, to how to buy a computer, to what food one should eat, the technique of having students construct expert systems as a cognitive tool is applicable across a very broad span of domain.

Wideman & Owston (1988) worked with 30 Canadian students in grade seven of a public school on a biological classification project. Where other researchers had used microcomputers in a stand-alone mode, Wideman & Owston chose to access an IBM 4341 mainframe via modem from microcomputers. Using an IBM proprietary software development environment that functioned much as an expert system shell, but with more powerful editing capabilities, students created expert systems within the limited domain of biological classification information provided in class. Wideman & Owston found that the students (no control group) were able to "complete tasks of greater cognitive complexity than is typically demanded of them in curricula for their age level, and to do so with a good degree of enthusiasm" (Wideman & Owston, 1988, p. 92).

Expert Systems to Teach Problem Solving

Another approach to using expert systems as a pedagogical tool is as a device for teaching problem solving. Lippert (1988) has noted that instruction in physics, using standard textbook problems, "usually cater only for the direct application of one or more previously learned formulas. In contrast, process problems foster critical thinking and creativity, since they require non-algorithmic strategies that integrate the various formulas and laws into a coherent unit" (Lippert, 1988, p. 24). Working with construction of knowledge bases in teaching quantum mechanics and physics to six freshman honors physics students, Lippert found that building expert systems changes students from "spectators in problem solving" (Lippert, 1988, p. 26) to "paraexperts" (p. 23) and creators of solutions, thus enhancing their higher-level thinking skills. With this small sample size, no control group was used.

Lai (1989) worked with 17 first-year nursing students in a project to build expert systems to help those students identify alcoholic patients. This learning experience contained elements of troubleshooting skills in the case of patients in denial of problems with alcohol and elements of diagnostic skills in the case of patients considered not to be accurately reporting their conditions. In addition to the primary learning goal, the study also investigated the degree to which the students developed a more complex set of problem solving skills, and the degree to which the students acquired conditional reasoning skills. Different from previously cited studies where each student constructed an expert system, the class together actually constructed one expert system, writing the rules communally during class sessions. Results pointedly stated that the principal focus of the study was not to create an expert system but to use creation of the expert system as a learning tool to foster improvement in the skills concerned with reasoning and problem solving. Lai found through this study, which did not include a control group, that there was enhancement of the reasoning skills and "acquisition of deeper understanding of the subject domain under study." (Lai, 1989, p. 16-17).

Expert systems have been used commercially in the field of accounting, as they have been in many areas of the business world for a number of years. Taking this tool of the field and putting it to different use, Bouwman & Knox-Quinn (1995) caused seven second-year students in an MBA program to create expert systems in an area of tax law called passive activity limitations. The specific function assigned the expert system was helping to determine whether or not an activity could be classified as active for tax purposes. Because of the small size of the group, no control group was used.

Bouwman & Knox-Quinn looked at creation of an expert system for classifying. The domain of the expert system construction was limited to materials provided in class. As a result of this study, Bouwman & Knox-Quinn affirmed that "student knowledge engineering" is "a viable instructional strategy" (Bouwman & Knox-Quinn, 1995, p. 246). They summed the results of this study into six observations:

1. A knowledge engineering project is a feasible project within the context of an accounting course . . .
2. Developing an expert system teaches students to read with a 'problem solving frame of mind' . . .
3. Developing an expert system teaches students how to structure and organize knowledge . . .
4. Developing an expert system teaches students how to communicate logically . . . in acquiring and structuring knowledge in a form suitable to be used in the construction of the expert system.
5. Developing an expert system increases students' domain knowledge . . .
6. Developing an expert system improves students' problem solving strategy (Bouwman & Knox-Quinn, 1995, pp. 237-242 and Knox-Quinn, 1995, pp. 252-256).

These six observations form a comprehensive example of, or prescription for, expert systems as mindtools used to foster higher order learning.

Mayer (1989) studied the creation of mental models in the domains of automobile brakes by novices with little or no prior knowledge about auto mechanics. Examining the differences in subjects who received textual information and one of the following four types of information: (a) graphics and labels, (b) labels only, (c) graphics only, (d) neither graphics nor labels, Mayer found that subjects who were presented graphics and labels in addition to text were better able to solve trouble-shooting problems and predict results from system changes than those who did not receive that information. The presence or absence of the graphics and labels did not enhance verbatim retention. Mayer's study formed one basis for this research.

<u>Mental Models</u>

Mental models are a distinct form of learning outcome, and can be thought of as mediator between perception and action (Rouse & Morris, 1985). Mental models can take numerous forms, either pictorial or symbolic, including propositional, visual, spatial, verbal, (Jih & Reeves, 1992) and device (Kieras & Bovair, 1984). Thus mental models are correspondent to reality rather than expressions of more formalistic approaches to thinking and learning, models of an existing state of affairs.

Mention of mental models can be found as early as 1943 in the writing of Craik (1943). Craik proposed that the brain was making small-scale working models of realities external to the person and possible actions. The individual could then internally process, or try out, various alternate courses of action, and decide which one was most favorable to the extant situation based on stored knowledge of varying degrees of similarity to the current situation.

Various concepts of mental models can be found in the writings of van der Veer (1990, p. 23). He noted that there are many different conceptualizations of mental models. Taking a simplistic approach, Staggers and Norcio (1993) defined mental models as objects and their relationships that are formed into structures. Redish (1994) expanded this explication to include not just relationships but rules of procedure and usage, images, and propositions. In terms reminiscent of "computerese", Glaser and Bassock (1989) have included in their definition of mental models the concept of "runnable mental simulations" constructed by individuals.

A wider interpretation of mental models shows them related to other types of knowledge representation in that the term "background knowledge" could be applied to foundational representations such as schema, where mental models would be the term applied to knowledge structures in use to plan, explain, or predict (Wilson and Rutherford, 1989). Similarly, Gentner and Forbus (1996) proposed that creating mental models during the learning process is essential if a person is to understand the "phenomena that are hallmarks of human cognition, including the ability to reason about complex physical systems, to make and articulate predictions about the world, and to discover causal explanations for what happens around us" (p. 2).

The concept of a mental model used in this study, is that of a multi-dimensional internal graphic and semantic representation of external objects, circumstances, or concepts, and their relationships and interactions to each other, that is created by an individual in the process of organizing, storing, and retrieving information. This places this study's definition of a mental model in the device model category (Haugeland, 1997). Jonassen & Tessmer (1996/1997) described this type of mental model as having four interconnected parts: knowing what, how, why, and when. This type of mental model may be acquired by learning the composition of the device, the relationship of its parts, and the functions of its subsystems.

The advances in the technology of hardware and software have served to broaden the application range of expert systems beyond that of strictly expert advisors or repositories expert knowledge for users to access as required. Their application has also been expanded into the role of cognitive tools, tools for learning (Knox-Quinn, 1995; Lai, 1989; Law & Ogborn, 1994).

In a departure from traditionalists like Piaget who postulated that reasoning was bounded by rules of logic, recent writings of Johnson-Laird (1994) and Bliss (1994) suggest that formal reasoning is the act of internally constructing mental models, as tools for thinking. With this variety of viewpoints on the definition or description of a mental model, there comes an equal diversity in proposed means of measuring mental models.

Mental Model Measurements

Mental models formed by learners are not visible to direct observation, thus techniques must be discovered to determine the presence of, and measure, this most complex of all types of knowledge. Different approaches to observing the presence of, and measuring, mental models in learners have been proposed by Itoh (1991):

- observing individual, pairs, or teams of learners using a piece of equipment singly or cooperatively,
- asking learners to explain or describe the use of a piece of equipment to another student or to an observer, and
- asking learners to make predictions about the behavior of a piece of equipment under conditions of alterations or

troubleshooting (p. 401).

Another measurement tool is the Pathfinder measure of conceptual networks. Building on earlier work of assessing structural knowledge, Goldsmith & Johnson (1990) were among the earliest to utilize the new Pathfinder techniques for evaluating student structural knowledge within a classroom setting. Working with undergraduate students in statistics classes, these researchers found that the Pathfinder techniques were predictive of examination performance.

Rowe, Cooke, Neville, & Schacherer (1992) studied several methods of measuring mental models. Using a domain of knowledge of automobile engines and both novice and expert subjects in that domain, Rowe et al looked at three techniques to measure existing mental models: (a) similarity ratings, (b) Pathfinder analysis, and (c) structured interviews. The researchers found convergence of results from all three measures and across novice and expert levels of expertise. That is, Pathfinder and similarity ratings predicted expert performance.

The Pathfinder measure is a tool to analyze proximity data by deriving network structures from that data. The networks Pathfinder creates are comprised of nodes, one per concept, and links, connections between the concepts. Links can be weak or strong and can be direct, from one concept to another, or indirect, from one concept through another to a third concept. From these networks, the PCKnot (Knowledge Network Organizing Tool for the IBM PC) software, which implements the Pathfinder procedures, offers a variety of calculated results including coherence, correlation, similarity, and average (Gonzalvo, Cañas, & Bajo, 1994). Figure 1 is an example of a Pathfinder network.

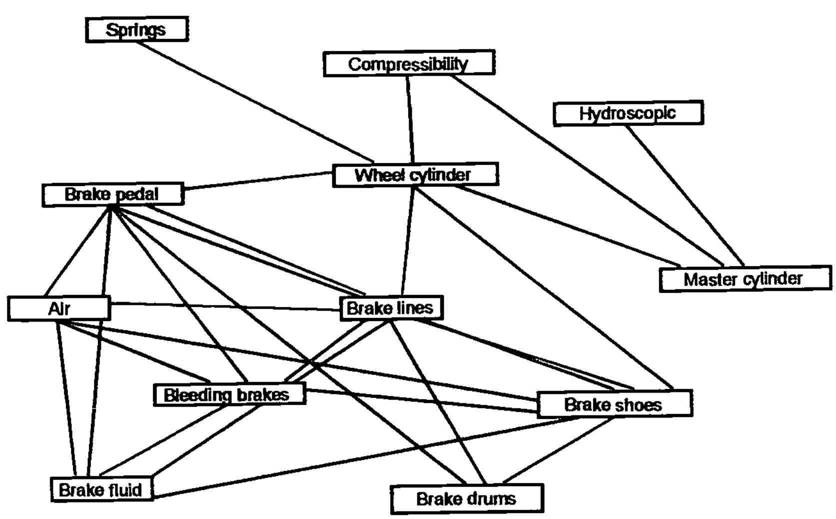

Figure 1. Pathfinder network using the concepts derived for this study.

Problem Summary

Mental model studies have looked at how individuals in several different age groups form mental models by virtue of several different learning situations and methodologies. Expert system studies have investigated the depth of processing of students as a result of creating expert systems on a variety of subjects. These studies, principally in the realm of problem solving, reported that students who created expert systems routinely processed information to a greater depth and in greater detail than students who learned by other techniques (Jonassen, Wilson, Wang, & Grabinger, 1993; Knox-Quinn, 1995; Lai, 1989; Law & Ogborn, 1994; Odom & Pourjalali, 1996).

While there are volumes of information contained in the research concerning, separately, both expert systems as mindtools to facilitate learning and methods for learning mental models, there is little about the two are combined. There is an occasional mention in the expert system literature of mental models, but that reference is to the formation of some sort of an internal picture of the expert system as part of the process of constructing the expert system. The formation of mental models of the domain in which the expert system is being built has not been mentioned. That is, no reference has been found of construction of an expert system leading to a mental model of anything other than of the system itself, and that only as a minor adjunct to the creation of the expert system.

METHODOLOGY

Research Question

Does creation of an expert system facilitate the formation of an accurate mental model?

Null Hypotheses

There will be no difference in mean measured mental models of a group of participants at the inception of the study (pretest), after reading textual material in the subject domain (midtest), and after creating an expert system on the domain subject (posttest), as measured by the following three measures:

1. There will be no difference in mean novice-expert network similarity scores, as measured by Pathfinder, on pretest, midtest, and posttest.
2. There will be no difference in mean scores on a system troubleshooting test on pretest, midtest, and posttest.
3. There will be no difference in mean scores on a test predicting system behavior on pretest, midtest, and posttest.

Domain

The domain selected was hydraulic drum brakes. This domain has a system of interrelated parts and functions, and thus is a device mental model (Kieras & Bovair, 1984).

Dependent Variable

The primary dependent or response variable measured was the presence of a mental model. The three separate measures that were used to gauge the presence and/or accuracy of the mental model were measurement of similarity from PCKnot, a Pathfinder program; a test of participants' troubleshooting abilities; and a test of the ability of participants to predict what the system would do when certain changes were made to the system.

Independent Variable

The explanatory or independent variable that was used in this study was creation of an expert system by each participant. This intervention was used to investigate if creation of an expert system would facilitate formation of a mental model.

Mitigating (moderator) Variable: Time Required to Create Expert System Induction Table

These data were collected by asking each participant, after completion of the work, approximately how many hours were spent creating the induction table. This particular variable was also investigated to determine if the amount of time spent makes this technique realistic for inclusion in classroom schedules. Time spent indicated that, with only limited classroom time available, these teaching strategies could be adapted to time available by adjusting the amount of content covered.

Participants

Participants for this study were 33 adult males and females ranging in age from 25 to 61, from a wide variety of professions, located throughout the United States, Canada, and the United Kingdom. The common threads among all participants were that the author taught them to use computers in general and expert systems in particular, and that they had no prior knowledge of hydraulic drum brakes. All were volunteers and refused any offer of compensation for their participation in this study.

Three other participants collaborated in forming the expert model network against which the networks of the participants were compared. These three individuals were internationally recognized experts in classic and vintage cars that have the type of brakes used as the subject domain in this study.

Materials

Text. Participants read passages on hydraulics and brakes. Adapted from World Book Encyclopedia (1994), the brake text and graphic (Figure 2) were the same information used by Mayer (1989) in the two experiments he conducted to investigate the effects of multimedia and graphics upon mental model development. By restricting the participants to using only the information, the size of the expert system and the amount of time required to construct it were limited to manageable sizes.

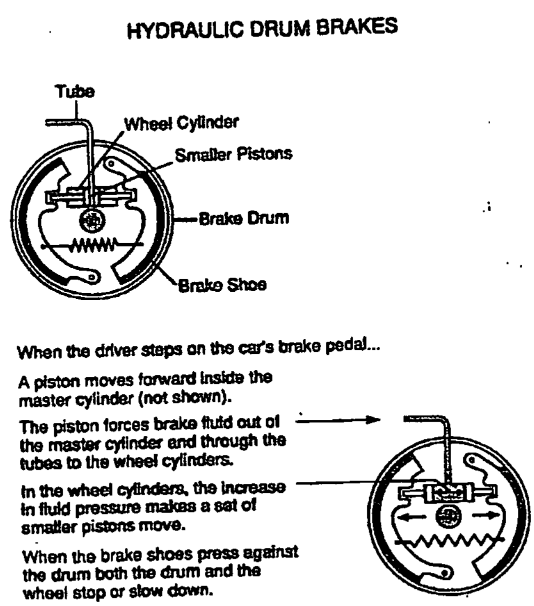

Figure 2. Hydraulic drum brakes (Mayer, 1989)

Expert System. The expert system software shell selected for this study was the latest available version (3.1 student) of VP-

Expert™. This particular software was selected for its auto-induction capability, its reasonable cost, and its compatibility with a wide range of Intel-platform personal computers. Auto-induction capability takes participant data in the form of a table and creates the expert system rules without the individual having to program each individual rule. This was a critical feature as it minimized cognitive load in constructing an expert system and frustration in using it as a learning tool. It also reallocates cognitive load to thinking about relationships among concepts and somewhat away from details of making a new piece of software operate.

Creating and running the expert system engages learners through auto feedback from the system, a motivational side effect (Pigford & Baur, 1995). This also expresses an advantage of expert system by induction over just creating a table similar to an induction table in a word processor.

Because of its ease of use, this particular software shell has been used, and is continuing to be used, in classrooms as a learning tool. Saleem and Azad (1992) used VP-Expert™ in their statistics learning experiment cited earlier. The software is in use today at Victoria University in Australia, Rutgers University, University of Akron, Bryant College, and California State University at Northridge, to name only a few institutions, as indicated by Internet postings of current course descriptions and syllabi.

Instruments

Prior to commencement of the study, levels of participant experience with computers and expert systems were collected electronically through self-rating scales. Demographic information on participant computer systems was used to design the network interfaces to ensure that information was provided to each participant in the text format of their word processor of choice. Three different measuring instruments were required for this study: PCKnot, troubleshooting test, and prediction test.

PCKnot. PCKnot software, acquired from its author, Roger Schvaneveldt of New Mexico State University, was used for measuring the structural representation of knowledge using Pathfinder techniques. An assumption of the PCKnot rating tests is that the organization of concepts in memory can be captured by a structural representation (Cooke & McDonald, 1987). That is, the organization of concepts in memory can be represented by a set of labeled nodes, each of which refers to a particular concept in memory, and the links between the nodes, which reflect the relationships between the various concepts.

The PCKnot measurement of similarity (NETSIM) computes the similarity between two Pathfinder networks (PFnets). This was used to compare the similitude between a participant's PFnet to the PFnet of the domain expert model (Schvaneveldt, 1998). Acton, Johnson, and Goldsmith (1994) used the Pathfinder procedure to measure similarity between expert and novice performance and to differentiate among levels of expertise. They also found that similarity has been a predictor of expert performance. Measurement of novice-expert similarity also addresses the accuracy of the participant's mental model of a system.

PCKnot requires participants to rate the similarity of pairs of concepts. These ratings are used to construct a Pathfinder network (Figure 2). PCKnot then compares the network of a participant to that of an expert to determine the similarity score. Similarity is determined by comparing the union and the intersection of concepts, and then it compares novice-expert concept "neighborhoods" to one another, not the entire structure. This means that it looks at local conceptual relations, not the global ones of multidimensional scaling (Gonzalvo, Cañas, & Bajo, 1994). Since mental models are composed of both concepts and the relations between concepts, this is a particularly appropriate tool to use in gauging a mental model (Rowe & Cooke, 1995).

Tessmer, Perrin, & Bennett (1998/1999) found that Pathfinder networks "can produce stable, coherent measures of structural learning, if properly applied" (p. 74). They further proposed that multiple administrations of the Pathfinder procedure could lead to increased reliability as raters "acclimate themselves to the Pathfinder interface and its conceptual task of pairing isolated concepts" (p. 66). In two studies, Kraiger & Cannon-Bowers (1995) found "construct-oriented evidence of validity" (p. 814) of structural assessment "as adapted for use in the evaluation of a training program for computer programming and a PC-based simulation of naval decision making" (p. 804).

Troubleshooting and Prediction Tests. These tests were developed by the researcher and a professor of instructional design. They were modeled after the troubleshooting tests of Itoh (1991) and Rowe & Cooke (1993), where students were asked to determine causes of alterations in system performance, and the prediction tests of Sasse (1991), where students were asked to predict the actions of a system when one or more of the system's components were changed. In investigating mental model performance, researchers have found that the ability of individuals to perform troubleshooting tasks and to predict the actions of a system when parts of that system are altered, are indicators of the presence (Lai, 1989) or use (Itoh, 1991; and Rowe & Cooke, 1995) of mental models.

The test of troubleshooting abilities required participants to determine what part of a system was causing it to malfunction and why. Research has shown that people who have an accurate mental model of a system know how parts of a model interact as well as what the parts are and why they operate in certain fashions (Green, 1990). Participants were given a set of matching questions and were asked to ascertain the cause and cure of each of the brake problems presented.

Detection and correction of system errors, even though not specifically taught, is an integral part of the models that individuals form (Jonassen & Tessmer, 1996/1997; Green, 1990). Different authors indicate that troubleshooting is a recognized measure of mental model acquisition and accuracy (Jonassen & Tessmer, 1996/1997; Green, 1990). For this reason, testing troubleshooting ability is appropriate to discovering the existence of a mental model in a subject domain. The matching test asked the participants the causes and solution to problems that might occur within the brake system (troubleshooting).

In the test of predicting abilities, participants were asked to predict system effect when a part of the system was altered. Among the tests investigated by Sasse (1991) to detect and measure mental models, was a prediction test. Sasse had participants in a study predict what a system would do after a modification had been made to the system. Sasse found that, as confirmed by other techniques of mental model measurement, prediction was an appropriate measure for a mental model. The prediction test in this study was developed by the researcher and a professor of instructional design, modeling it after the Sasse prediction tests. Participants were given a set of multiple-choice questions and were asked to predict what would happen and why, when changes were made to the system.

Jonassen and Tessmer (1996/1997) also found that individuals who formed mental models in a domain of knowledge also evidenced abilities of prediction in addition to inference and interpretation. They referred to predictive ability as a payoff of mental model learning as well as a measure of learning outcomes. The multiple-choice test asked the participants to predict changes in the operation of the brake system as a result of a change in one of the system's parts.

Setting. The setting was the home or office of each participant, using their existing personal computers. Participants were not restricted to a particular time frame for submissions, but were encouraged to work with as much speed as possible. From wherever the participants worked, a variety of communication protocols were used: telephone, mail, e-mail, fax, and direct computer link.

There were dedicated, data-rate, toll-free telephone lines available during the data collection portion of this study. Each participant had an access code that permitted connection both to the mainframe computer for data transmission and to the author's telephone for voice communications via a mainframe link. There was a dedicated area of a mainframe computer set up with these communications protocols for the use of participants during the period of the study. Data collected by the mainframe was transmitted on a scheduled basis or on demand to the author's personal computer.

Procedure.

The timeline in Figure 3 graphically displays the procedural sequence followed for this study.

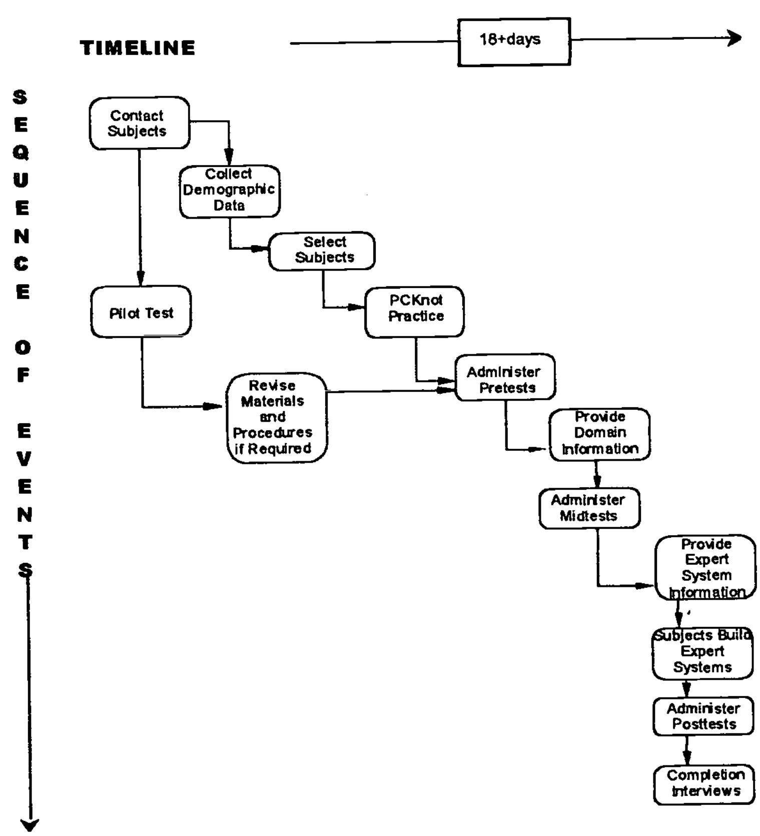

Figure 3. Timeline of participant selection, materials preparation, and data collection.

Potential participants were contacted to ascertain their availability and willingness to participate in the survey. Signatures on consent forms were secured. Participants were asked to fill out an electronic biographical form, which automatically entered that information into the database for this study. The submitted information was screened for any information that would indicate that the individual would be inappropriate for the study due to prior knowledge of brake systems or lack of prior experience with VP-Expert™ software. Data on domain knowledge and expert system experience were reviewed. Based on data submitted, non-qualifying participants were eliminated.

Eight individuals participated in the pilot tests. Two reviewed the materials for readability and three critiqued the troubleshooting and prediction tests. Changes were made based on their recommendations. Three experts selected the 12 concepts (Tessmer, Perrin, & Bennett, 1998/1999), and then used PCKnot software to create an expert network. The averaging computation of the PCKnot software was used to combine the three experts' networks to create the expert model that was used for the study. When averaging, PCKnot creates a new proximity data file of the average of two or more proximity data files as it "averages the elements of multiple data matrices to obtain a new, average, data matrix." (Schvaneveldt, 1998, p. 6) Averaged expert networks have been used by Acton, Johnson, & Goldsmith (1994) to study the acquisition of mental models / structural learning.

The participants practiced on a trial PCKnot data set of five concepts. These concepts were common office terms familiar to all participants through daily use. The purpose was to familiarize participants with the pair rating process, and to introduce the PCKnot screens that they would see when they did the pair ratings on the hydraulic drum brake concepts.

After the brief practice session with PCKnot, the participants took the first of the three PCKnot tests using the 12 hydraulic drum brakes concepts selected by the experts. Participants were also given the troubleshooting and prediction pretests. Upon completion of the first PCKnot test, participants were provided with text and graphic domain information, electronically transmitted. They were permitted to read the information on screen if they chose, and to proceed immediately to the next round of tests. The information was also automatically downloaded to their computers to be available to them while they were building the expert system. Either immediately after reading textual material or at next logon participants completed PCKnot pairs ratings, troubleshooting, and prediction midtests.

When the three midtests were completed, information and instructions for constructing the expert system were electronically transmitted to each individual, and access to the expert system shell on the network was made available. The task was to use the domain information to create a simple expert system to diagnose problems of hydraulic drum brakes and recommend fixes for the problems. Participants created an induction table for the expert system. They then logged onto the network, and using the VP-Expert™ auto-induction capability, caused the VP-Expert™ software to create the expert system rules from the induction table they had created. Then the participants tested their expert system by running it as many times as they chose. To create the induction table, participants had to understand both the overall function of the brake system, the functions of its separate parts, and some hydraulic concepts.

After creating a working expert system, participants completed the final PCKnot rating test and took the final troubleshooting and prediction tests. As the last part of the final prediction test, participants filled out a short questionnaire about their experiences in participating in this study. When final test results had been received, participants were interviewed via telephone for their comments concerning this study. This was an unstructured, informal interview.

Research design

Because there was no random assignment and only one group of participants, the design used was an exploratory design. While use of a control group would have added a measure of control of threats to validity, the size of the available population meant that a control group could not be used without sacrificing statistical power. Gall, Borg, & Gall (1996) wrote that the "one-group pretest-posttest design involves three steps: (a) administration of a pretest measuring the dependent variable; (b) implementation of the experimental treatment (independent variable) for participants; and (c) administration of a posttest that measures the dependent variable again." (p. 491). They further stated that "the one-group pretest-posttest design is most justified when extraneous factors can be estimated with a high degree of certainty, or can safely be assumed to be minimal or nonexistent." (p. 493). By designing the procedures for this study to minimize the effects of extraneous factors, the exploratory design meets the Gall, Borg, & Gall criteria.

Lehrer, Erickson, & Connell (1994) used a one-group pretest-posttest design with 20 ninth-grade students in an American history class. In their study, Lehrer, et al. used the HyperAuthor™ computer program as a mindtool "to stimulate students' own conceptual organization" (p. 237). Knox-Quinn (1995) used a one-group pretest-posttest design in her study involving seven second-year MBA students. In that study, students constructed expert systems to learn about elements of tax accounting.

Network similarity data from PCKnot software was used to investigate changes in mental models of participants from pretest to midtest to posttest. The fit of the individual's Pathfinder network to the expert network provided by the domain experts was also examined and analyzed. Troubleshooting and prediction test data were used to triangulate the results of the Pathfinder techniques. The types of data collected, their sources, and the format of each type of data are contained in Table 2.

Table 2

Sources and Formats of Data

DATA	SOURCE of DATA	FORMAT of DATA
Similarity	Pathfinder Pretest, Midtest, & Posttest	Continuous –1 to1
Troubleshooting test	Pretest, Midtest, & Posttest	Integer 0 –10
Predicting test	Pretest, Midtest, & Posttest	Integer 0 -10
Time to complete expert system	Reported by participant	Number of hours

Data Analysis Methods. SPSS statistical software was employed for data analysis. Data were analyzed using the General Linear Model (Gall, Borg, & Gall, 1996).

RESULTS

Learning Achievement Hypothesis 1

Hypothesis $H1_0$ stated that there would be no difference in novice-expert network similarity scores, as measured by Pathfinder network techniques, before and after participants create an expert system. Table 3 presents the means and standard deviations of similarity scores of participants' Pathfinder networks to the expert model network at the beginning of the study (pretest), after participants had read textual information on the subject domain (midtest), and after creating an expert system (posttest).

Table 3

Mean Scores of Learning Gains from Pretest to Midtest and Midtest to Posttest: Pathfinder Network Similarity (N = 33)

Novice-Expert Similarity Scores	Pretest	Midtest	Pretest → Midtest Gain	Posttest	Midtest → Posttest Gain
M	.173	.176	.003[a] (1.7%)	.389	.213[b] (121.0%)
SD	.005	.006		.006	

Notes: Similarity scores can range from –1.00 to 1.00. [a] $p = .836$ [b] $p = .000$

Similarity scores and the changes in scores from pretest to midtest to posttest are graphically presented in the box-and-whisker plot in Figure 4. This representation summarizes the degree of variability or dispersion in the data it presents (Garrett, 1958). This representation summarizes the degree of variability or dispersion in the data it presents (Garrett, 1958). The box and whisker plot indicates that there was a substantial difference between midtest and posttest score medians and ranges, with the lowest score on the posttest higher than the highest score on either the midtest or the pretest. Based on scores achieved and statistically significant results, hypothesis $H1_0$ was rejected.

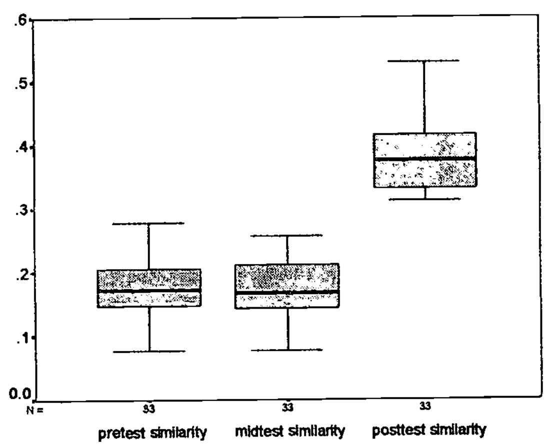

Figure 4. Box and whisker plots of pathfinder similarity scores

Learning Achievement Hypothesis 2

Hypothesis $H2_0$ stated that there would be no difference in scores on a troubleshooting test before and after participants create an expert system. Table 4 presents the means and standard deviations of participants' troubleshooting test scores at pretest, midtest, and posttest.

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Table 4

Mean Scores of Learning Gains from Pretest to Midtest and Midtest to Posttest: Troubleshooting (N = 33)

Troubleshooting Test Scores	Pretest	Midtest	Pretest → Midtest Gain	Posttest	Midtest → Posttest Gain
M	1.00	2.14	1.14[a] (113.6%)	7.28	5.14[b] (240.5%)
SD	1.08	1.08		1.44	

Notes. Maximum score = 10. [a] $p = .001$ [b] $p = .000$

Troubleshooting test scores and the changes from pretest to midtest to posttest are graphically presented in Figure 5.

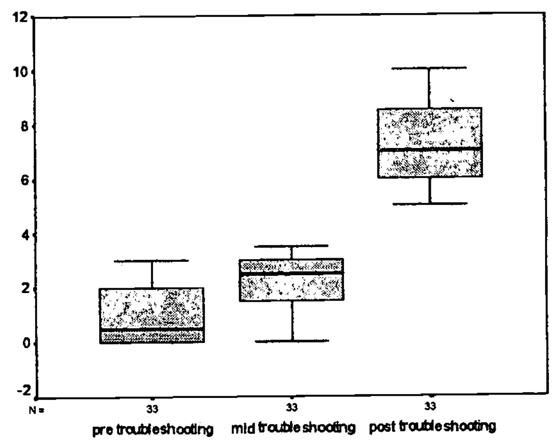

Figure 5. Box and whisker plots of troubleshooting test scores

The box and whisker plot indicates that there was a substantial difference between midtest and posttest score medians and ranges, with the lowest score on the posttest higher than the highest score on either the midtest or the pretest. Based on scores achieved and statistically significant results, hypothesis $H2_0$ was rejected.

Learning Achievement Hypothesis 3

Hypothesis $H3_0$ stated that there would be no difference in scores on a test predicting system behavior before and after participants create an expert system. Table 5 presents the means and standard deviations of participants' prediction test scores at pretest, midtest, and posttest.

Table 5

Mean Scores of Learning Gains from Pretest to Midtest and Midtest to Posttest: Prediction (N = 33)

Prediction Test Scores	Pretest	Midtest	Pretest →Midtest Gain	Posttest	Midtest → Posttest Gain
M	1.21	2.59	1.38[a] (113.8%)	7.85	5.26[b] (202.9%)
SD	1.14	1.27		1.73	

Notes. Maximum score = 10. [a] $p = .001$ [b] $p = .000$

Prediction scores and the changes in scores from pretest to midtest to posttest are graphically presented in Figure 6.

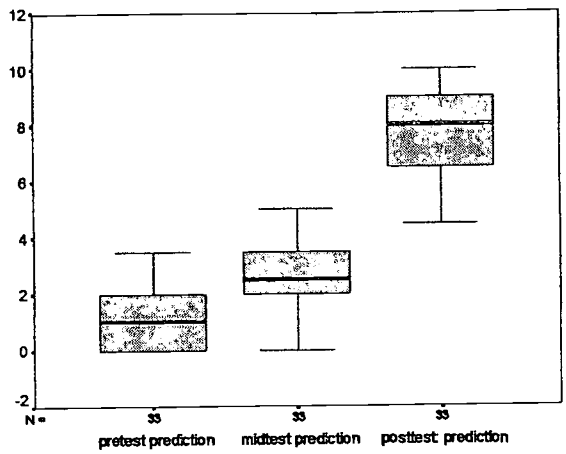

Figure 6. Box and whisker plots of prediction test scores

The box and whisker plot indicates that there was a substantial difference between midtest and posttest score medians and ranges, with the lowest score on the posttest higher than the highest score on the pretest and only one half of a point lower than the highest score on the midtest. Based on scores achieved and statistically significant results, hypothesis $H3_0$ was rejected.

A one-way within-subjects repeated-measures analysis of covariance (ANCOVA) was conducted for each of the three tests. The factor was the pretest, midtest, and posttest administration of tests, the covariate was the amount of time spent constructing the expert system table, and the dependent variable was the Pathfinder similarity scores, the troubleshooting test scores, and the prediction test scores. The results for the three ANCOVAs are presented in Table 6. The results indicated that there was a statistically significant difference in scores on all three tests among test periods after controlling for time. This connoted a definite learning gain during the period of the study, as shown by the results of each of the three different tests.

Table 6

Repeated Measures ANCOVA Results from Similarity, Troubleshooting, and Prediction Tests

	PCKnot Similarity Scores	Troubleshooting Test Scores	Prediction Test Scores
F (2, 30)	20.561	32.374	26.789
p	0.000	0.000	0.000
$\eta^{2\,a}$	0.578	0.683	0.641

a. Cohen (1988) stated that, for ANCOVA, small effect size = 0.10, medium effect sized = 0.25, and large effect size = 0.40 (p. 284-286).

As follow-up to the repeated-measures ANCOVAs, paired sample t-tests were conducted to evaluate the learning gain from pretest to posttest and to ascertain whether there was greater learning gain from pretest to midtest or from midtest to posttest. The results of these paired sample t-tests are presented in Table 7. In each of the three measures, that there was a substantially larger learning gain in the midtest to posttest interval than there was in the pretest to midtest interval.

Table 7

Follow-up *t*-test Results from Similarity, Troubleshooting, and Prediction Tests

	PCKnot Similarity Scores			Troubleshooting Test Scores			Prediction Test Scores		
	Pretest → Midtest	Midtest → Posttest	Pretest → Posttest	Pretest → Midtest	Midtest → Posttest	Pretest → Posttest	Pretest → Midtest	Midtest → Posttest	Pretest → Posttest
M	0.0003	.213	.216	1.136	5.136	6.273	1.379	5.258	6.636
SD	0.008	.007	.008	1.185	1.981	1.635	1.888	2.229	2.130
t(32)	0.208	16.547	15.713	3.535	14.891	22.039	4.196	13.547	17.901
p	0.836	.000	.000	.001	.000	.000	.000	.000	.000
d [a]	0.036	2.880 (large)	2.736 (large)	.615 (medium)	2.593 (large)	3.837 (large)	.730 (medium)	2.359 (large)	3.115 (large)

a. Cohen (1992) stated that, for *t*-tests, small effect size = 0.20, medium effect sized = 0.50, and large effect size = 0.80 (p. 156-157).

Other Results

Post Study Survey. In addition to the measurement of learning gains through Pathfinder procedures and test scores, participants were queried about their experiences in the study, and were asked to rate, on a scale of 1 to 5, problems with the network and the Pathfinder procedures, increase in knowledge about brakes, usefulness of building the expert system, and amount of time spent creating the expert system table. The responses indicated that the participants had little problems using the network or the PCKnot software. Participants reported that they had experienced an increase in knowledge in the subject area, a perceived learning gain supported by the results of Pathfinder procedures and test scores. Participants reported that creating the expert system was very helpful in achieving the knowledge gain. Participants estimated that they spent an average of 4.86 hours (range of 2.0 to 8.0 hours) to create the expert system.

General Participant Comments. A final question was posed to participants in the posttest questionnaire, after they had completed the study, "What else would you like to tell me about this experience?" Within a week after completion, participants were also queried telephonically about their thoughts on the study. Expressions of learning in different / better ways, of enjoying themselves, and of eagerly awaiting results were the dominant types of comments received. The comments received as a result of the posttest questionnaire and telephone interviews were categorized and are presented in Table 8.

Participant comments collected in the posttest survey questionnaire and in the telephone interviews after completion of the study were strongly supportive of the quantitative results of the study. Problems reported were quite minor in nature and few in number, and consisted primarily of what participants referred to as operator error. Participants, with very good humor, reported failing to read screen instructions, pushing the wrong key, clicking on the wrong box, clicking when keystrokes were needed, or not following instructions. No participant voiced concern that missed instructions were confusing or burdensome.

Table 8

Freeform Comments Concerning the Study (Numbers following comments indicate number of iterations of that comment.)

Category	Comments
Cognitive Processing – Concentration & Attention	Made me read more carefully / more times when making the expert system than I usually do. (13) Really made me think. Required that I exert greater concentration than it usually takes for me to read technical material.
Cognitive Processing – System Decomposition	Caused me to decompose the information in a way that I don't usually do when learning something new. Had to take the brake system apart (virtually of course) and conceptualize how the parts worked to put it all together in the expert system.
Cognitive Processing – Alternative Approaches to Thinking	Required me to organize the information / organize much more logically than is my normal procedure. (3) Showed me a different way to think about learning. Food for both the left and right brain – maybe a way of making them work together better. To do troubleshooting made me think and learn differently and more comprehensively.
Learning Attitudes – Enjoyment	Fun / had fun / fun experience / lots of fun. (19)
Learning Attitudes – Satisfaction	Really felt good / sense of accomplishment / really felt like I did something to run my expert system. (3) Thought this would be just an academic exercise, but I really learned something useful. Learned something about what computers can do as well as about brakes. Being a guinea pig is different from what I had envisioned – I liked it. Feel more confident about talking to my mechanic about my brakes. (4) How about doing other car systems? – I volunteer. Liked learning in a whole new way. Have always had trouble memorizing but this made learning the pieces and/or the movements easy. (2) Why didn't someone think of this when I was in school – beats lecture. Not at all what I expected but a positive experience.
Interest in the Study	Looking forward to my copy of the results. (17)
Miscellaneous	Where can I get a copy of that software? Would like to work some more with it. May want to use technology in my business / corporate training program. (2) Glad I could help.

The most serious problem reported was the five comments that there were too many pairs to be rated in each of the three PCKnot tests. The number of rating pairs were variously described as boring, irritating, and why all combinations and not just selected ones. When queried after the study, participants indicated that the number of pairs to be rated did not deter them from giving the same attention to each of the pairs, but that had there been any more, they might well have succumbed to the temptation to just tick off numbers at random and be done with it. This aped results of one of the pilot tests that found that more than 11 or 12 concepts resulted in decreased diligence on the part of participants in doing the ratings, that 11 to 12 concepts was the boredom threshold. Rowe & Cooke (1995) cautioned that "presenting all pairs in a concept set quickly leads to an unmanageable number of pairs as the number of concepts increases" (p. 253). They further observed that "even with a smaller number or concepts (around twenty), the pairwise ratings task may seem quite long and tedious to subjects (p. 253)." Future studies using PCKnot should carefully consider the number of concepts used.

In addition to indications of positive gains in knowledge of the subject domain from the three measurements, participants reported that they felt that they knew substantially more about brakes after completion of the study. From initial unanimous zero scores on the five-point rating scale of knowledge of automobile brakes, participants' self-ratings increased to a mean posttest score of 3.45. This provided further evidence of the effectiveness of expert systems as mindtools.

Reinforcing the increased self-perception of knowledge gain, participants enthusiastically reported that they found the process of creating the expert system to be both fun and very helpful in learning the material. The mean score on the five-point rating scale of the helpfulness of building the expert system in acquiring knowledge was 4.61. This indicated a substantial approval on the part of the participants of the technique as useful to them in acquiring knowledge.

Summary of Learning Achievement Hypothesis Data

The data collected in this study showed significant positive differences in the scores on all three measures from pretest to posttest. The data also evinced significant positive differences in scores on all three measures from midtest to posttest. The statistics for pretest to midtest indicated mixed results.

DISCUSSION

This study investigated the use of an expert system as a mindtool, and whether or not creating a simple expert system would facilitate the formation of an accurate mental model of a system. The results of this study indicated that, in the individuals participating in the study, creating the expert system substantially increased participants' scores on all three measures of mental models. Moreover, participants indicated that using the expert system focused their attention on the topic and was fun to use.

Network Similarity

The use of an expert system facilitated the development of more expert-like knowledge structures in participants, as measured through network similarity. Network similarity scores increased a non-significant amount during the pretest to midtest period in which the participants read materials about the subject domain. However, network similarity scores increased significantly, with a "large" effect size (Cohen, 1992), during the midtest to posttest period in which the participants created an expert system in the subject domain. Participant mean novice-expert posttest similarity rating was .389 out of a possible 1.000. Expert-expert combined similarity rating was .666. While participants improved significantly, there was still much more that they could learn. Although the participants' conceptual networks grew closer to those of the experts, and their cognitive structures became more like the expert model, there was still a gap between the knowledge the novices attained and the knowledge of the experts.

These results were similar to those found by Odom & Pourjalali (1996) who noted that constructing an expert system resulted in greater learning gains in concepts than traditional instruction. Bouwman & Knox-Quinn (1995) also wrote that "developing an expert system increases students' domain knowledge"(p. 241). They found that, as students advanced through a course, the way students knew structures came to more closely resemble the way experts knew structures.

Troubleshooting Test

The use of an expert system facilitated the development of more expert-like knowledge structures in participants, as measured by the troubleshooting test. Troubleshooting test scores increased significantly, but with only a "medium effect size

(Cohen, 1992), during the pretest to midtest period in which the participants read materials about the subject domain. However, troubleshooting test scores increased a greater amount, with a "large" effect size (Cohen, 1992), during the midtest to posttest period in which the participants created a small expert system in the subject domain. The mean of participants' posttest troubleshooting test scores was 7.28, compared to the 2.14 mean of their troubleshooting scores on the midtest. With a potential score of 10 on the test, it can be seen that while participants made a significant learning gain, there is still more that they can learn.

Troubleshooting ability is a commonly acknowledged measure of mental models. The results in this study are similar to those of Lai (1989) who found that creation of an expert system facilitated development of troubleshooting skills. These results indicated that student construction of an expert system enhances system troubleshooting skills, indicating the development of an accurate mental model. Rowe & Cooke (1993) also found that troubleshooting tests were confirmatory of Pathfinder procedure results and that "mental models are assumed to play an important role in facilitating most human-equipment interactions, particularly when the equipment does not behave in an expected manner" (p. 244).

Prediction Test.

The use of an expert system facilitated the development of more expert-like knowledge structures in participants, as measured by a prediction test. The average of prediction test scores increased significantly during the pretest to midtest period in which the participants read materials about the subject domain, but with only a "medium" effect size (Cohen, 1992). However, prediction test scores increased significantly, with a "large" effect size (Cohen, 1992), during the midtest to posttest period in which the participants created a small expert system in the subject domain. The mean change of participants' posttest prediction test scores from the midtest was 5.26, compared to the 1.38 mean change of their prediction scores from the pretest to the midtest, or almost four times as great an increase. With a potential score of 10 on the test, it can be seen that while participants have made a significant learning gain, there is still more that they can learn.

These results are similar to Itoh's (1991) observations that measurement of mental models can be accomplished through assessing learners' ability "to make predictions about the behavior of a piece of equipment under conditions of alteration" (p. 401). Goldsmith & Johnson (1990) found a strong positive correlation between Pathfinder scores and tests of predictive ability. Prediction, as they used it, referred to the ability of an individual to predict the reaction of a system to a change of state of any part of the system. This study also indicated that the two scores were positively correlated ($r = .818$, $p = .000$). Using the expert system, participants seem to have developed more expert-like mental models that improved their prediction performance.

Overall Results.

The results of developing an expert system, when it is used as a mindtool, is apparently the development of more expert-like mental models of the subject domain in which the expert system is created. Jonassen (1995) asserted that "Lippert, among the early advocates of expert systems as cognitive tools, argued that asking students to construct small rule bases is a valuable method for teaching problem solving and knowledge structuring for students from sixth grade too [sic] adults" (p. 59). When used as a mindtool, an expert system becomes a process, not an end product. It is a means to a learning gain by engaging students, fostering their concentration, and assisting them in organizing information.

Recommendations

Teachers. Learning gains resulting from student-constructed expert systems are well documented in the literature, however the other studies were measured in terms of outcomes other than mental models, such as problem solving (Lai, 1989; Tamashiro & Bechtelheimer, 1991; Lippert, 1988; Law & Ogborn, 1994). Other researchers have found that students engaged in deeper processing of knowledge (Kieras & Bovair, 1984), organized information more logically (Bouwman & Knox-Quinn, 1995; Knox-Quinn, 1995; Willie, 1990), and demonstrated increased problem-solving abilities (Law, 1995) as a result of learning by constructing of expert systems.

This study's results were confirmatory of those findings, and in addition, showed that such learning gains can be assessed by measuring the change in participants' mental models through several complementary measures. It is therefore reasonable to expect that both of these techniques, construction of an expert system and measurement of mental models through the Pathfinder technique, should be included in the repertoire of both teachers and instructional designers.

This technique may be particularly useful for teaching systemic concepts, or for learning how things work together. For example, Okamoto, Kawashima & Miyame (1994) used expert systems in teaching elementary school students about environmental problems in a city and deciding what a city mayor would do with various elements of the infrastructure. Wideman & Owston (1988) used this technique to teach biology classifications of "birds, fish, plants, insects, mammals, arthropods, and amphibians and reptiles" (p. 90) to grade seven students. In both cases students had to learn to concepts, concept relationships, or problem-solving, making them a candidate for using expert systems as a mindtool for forming student mental models.

Using an expert system in a learning situation requires the teacher/trainer to have the additional skills to teach construction of a small expert system, to determine which subject domains are appropriate for teaching by this technique, and to measure the mental model learning outcomes. Thus expert system instruction should be included in future teachers' curricula. With a moderate level of prior computer knowledge, learning to use expert system software should be no more difficult than learning other computer-based mindtools such as spreadsheets or databases, and it should take no more time.

Expert system software is readily available, bundled with a variety of texts currently in print. These texts include instruction on how to construct an expert system, and are tailored to various disciplines, such as mathematics, business, or computer science. Cost of the software / text packages is moderate. This study showed that the average time to construct the induction table was less than five hours for 12 concepts. So, for a minimal investment of time and money, including the teacher's time invested in learning to use the software, this technique could be implemented in a classroom. Using fewer concepts could reduce class time for this, or help sustain attention in younger learners.

The auto-induction capability, which takes participant data in the form of text or a spreadsheet table and creates the expert system rules without the student having to write each individual rule, is a critical feature. It minimizes students' cognitive load in constructing a system and frustration in using it as a learning tool. Students simply have to create the induction table, and then benefit from the feedback provided by the expert system.

If Pathfinder techniques are used to assess mental models, care should be given to the number of concepts selected for rating. As shown by this study, too many pairs elicit complaints from raters and give rise to possible boredom or inconsistent care in doing the ratings.

Instructional Designers. These expert system techniques would be appropriate for inclusion in the toolkit of instructional designers. However, not all instructional or training applications or situations would be appropriate for use of the expert system creation method. This strategy would be most applicable when designing for outcomes such as problem-solving ability, ability to decompose and reassemble systems, or understanding of systemic component relationships are sought.

The expert system technique has been successfully applied across a wide spectrum of learners from grade 2 (Tamashiro & Bechtelheimer, 1991), to high school (Conlon & Bowman, 1995), to undergraduate (Lai, 1989), to graduate school (Bouwman & Knox-Quinn, 1995). Wideman & Owston (1993) found that such a teaching procedure was especially effective in students with higher than average abstract reasoning scores.

One item necessarily included in instructional designer training would be that mental models are a legitimate learning outcome, distinct from problem solving or concepts learning outcomes. Jonassen and Tessmer (1996/1997) have constructed a new taxonomy for designers that stipulated that mental models are a distinct learning outcome. Incorporation of this taxonomy into instructional design curricula would provide a structure on which to build such training.

When and how to include this delivery of instruction technique would necessarily need to be incorporated in instruction or training for instructional designers. To incorporate these techniques into instructional design, students would have to learn where it would be applicable, to whom it would be most beneficial, and how to use the various mindtools.

CONCLUSION

This study examined the proposal that, using a mindtool in a constructivist learning environment, participants would create an accurate mental model of the subject matter being studied. Results achieved by participants from creating the expert system mirrored results achieved by a variety of researchers in a range of age groups and subject matters. Differing from other studies, the learning outcome measured in this study was formation of a mental model and the comparison of participant mental models to the mental models of experts.

Expert systems are only one of a number of potential mindtools, each with its own potential niche(s) in teaching and learning. Expert systems are probably the most versatile and powerful of these tools, but require the most skill on the part of instructional designers or teachers to use them appropriately.

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